DISCERNING PROPERTIES OF A SELF-ORGANIZING NETWORK (SWARM) SHAPING ITS STRUCTURE, FUNCTION, AND RESILIENCE

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ABSTRACT

Advancing the development of a net-centric Army depends on our ability to understand the benefits and costs of information flow through networks. Networks can vary in composition and expanse, with a variety of examples present in daily life (e.g., the internet, acquaintances, animal groups). The functionality of a given network generally depends upon the connectivity among its constituent members (nodes). As with acquaintances and popular web sites, these connections often change over time. Most network analyses focus on static systems using snapshots of data taken in time. Investigators then search for correlations between the degree of connectivity within the network and the network's ability to resist interference (i.e., noise) or external perturbation (e.g., power loss, attack). We seek insight into the capability of network analysis to discern properties of a dynamic network (of collective behavior) shaping its structure, function, and resilience using swarming behavior as our model system. Specifically, in this paper we begin answering the question: how many neighbors should an individual in a networked swarm track for maximum efficiency of information transfer, critical to survival under attack and failure scenarios.

Through numerical systems based on ecological theory we seek to better understand networked collective behavior, e.g., susceptibility to outside attack, which can be used to guide the engineering design of artificial networks. We believe this work presents an opportunity to mine the assets of ecology for improved development of disruptive technologies and a net-centric Army.

1. INTRODUCTION

Most networks rely for their function on their connectivity, i.e., the existence of paths leading between pairs of individuals (Newman, 2003). Interaction among individuals (collective behavior) has proven to be an evolutionarily robust tactic in mobile organisms and the resiliency of this tactic to environmental perturbation and noise is exceeded only by its prevalence across taxa. Animals often organize as a network shaped by evolutionary pressure for survival that can react differently to various density-dependent (e.g., prey availability) and density-independent (landscape complexity) factors. Structure of an animal group is fundamental to its biology, influencing its pathways of information transfer and the way that the population exploits its environment (Lusseau et al., 2006). In ecology, swarms are a group of networked individuals, with the main goal of the interaction among individuals being the maintenance of cohesion in the face of strong perturbations, of which predation is the most relevant (Ballerini et al., 2008).

The numerical analysis of swarms is based on the premise that individuals align and attract each other, with interaction decaying with increasing distance between individuals. To date, the vast majority of swarm models – and resulting theory – are based on the definition of "distance" as "metric distance": individuals follow a correlated random walk with specified, non-overlapping behavioral zones with the highest priority for individuals being maintenance of a minimum distance between themselves at all times to avoid collisions. Individuals move away from others within a close-range spherical "zone of repulsion" with radius r_d. Individuals align with others outside r_d but within a "zone of orientation" with radius r_o and are attracted to individuals outside r_o but within a "zone of attraction" with radius r_a (Couzin et al., 2002; 2005). While interaction based on metric distance seems natural given the sensory systems of many swarming species, it is unable to reproduce the density

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changes typical of animal aggregations because cohesion is lost when mutual distances become large compared with the interaction range (Ballerini et al., 2008).

Noting that structure is the foremost effect of interaction, and, conversely, interaction is ciphered in the inter-individual spatial structure, Ballerini et al. (2008) offer empirical and modeling results to support an alternative theory of “topological distance”. Topological distance is the number of intermediate individuals separating two individuals, not how far apart they are, with each individual interacting with a fixed number of neighbors irrespective of their metric distance. The crucial difference between metric and topological interaction comes in when the density varies: in the topological case, two individuals 5 m apart in a sparse flock attract each other as much as two individuals 1 m apart in a denser flock provided the number of individuals between the two is the same.

Theoretically, topological distance is more suitable for maintaining cohesion in the face of strong density fluctuations and strong perturbations, including predation (Ballerini et al., 2008). While tracking more neighbors provides redundancy against misinformation and robustness against loss of transmitting neighbors, it comes with additional bioenergetic and cognitive processing costs necessary to resolve conflicts.

The ability to track individuals (numerosities) decays beyond a certain number and range of perception. The literature has yet to settle on a fixed number of numerosities, but the maximum range is generally suggested as three to seven: six to seven (for birds; Emmerton and Delius, 1993; Ballerini et al., 2008), three to five (for fish; Tegeder and Krause, 1995), three to five (based on numerically modeling of collective behavior; Inada and Kawachi, 2002), and three to four (based on limits of visual working memory; Luck and Vogel, 1997; Vogel et al., 2001; Bays and Husain, 2008). An improved understanding of the topological distance associated with maximum efficiency of information transfer is critical to the engineering design of bio-inspired artificial networks. Towards this end, three critical questions emerge: (1) how many neighbors should be tracked for maximum efficiency of information transfer, (2) how are the few neighbors tracked discerned from the collective of many neighbors, and, later, (3) what tradeoffs exist for (1) and (2) under attack and failure scenarios. To simplify the problem at this stage we assume all individuals are within the range of perception.

To explore (1) and (2), we employ a two-pronged approach. First, we merge concepts from neuroscience, sensory biology, optics, and physics to develop a first-principles based algorithm of swarming behavior. Our swarm model uses elementary optical information processing to infer traffic rules within the collective. Employing optical rules facilitates improved biological realism over existing swarm models, and allows us to explore the rate of information transfer using a bottom-up, mechanistic approach (Lemasson et al., 2008). This approach is applicable to many taxa as well as to artificial sensor networks. Second, in this paper, properties of these self-organized networks are analyzed using a top-down approach based in network theory to discern the theoretical maximum rate of information transfer according to topological distance.

The two-pronged approach explores the attributes of ecological swarms from two sides. The bottom-up, mechanic approach affords, and burdens, the analysis with elements of animal sensory ecology important to taxa that swarm. In this paper, the top-down approach does not account for sensory ecology at the individual level; it strictly analyzes the theoretical potential of information transfer. In other words, network analysis of our numerical swarms should provide some guidance into the theoretical potential of information transfer. This potential is then subject to the benefits and costs imposed by ecology (Lemasson et al., 2008). Specifically, information in real systems transfers imperfectly so real systems may require more redundancy than is ‘theoretically’ required to achieve a certain level of performance. On the other hand, information in real systems may transfer through pathways not immediately intuitive from the perspective of a top-down analysis.

2. METHOD

To discern the theoretical maximum rate of information transfer as a function of topological distance, we employ analyses based in network theory. We apply our analyses to four numerical, simulated swarms embodying sensory and emergent properties of real swarms (Lemasson et al., 2008). Specifically, we seek to corroborate or challenge existing values of topological distance cited in the literature.

2.1 Terminology

The ecological and network literature are fraught with inconsistent terminology. To assist the reader in navigating the terminology, we make the following equivalences:

Group = *Network* = *Graph*
Subgroup = *Subnetwork* = *Community*
Individual = *Vertex* = *Node*
Relationship = *Link* = *Tie* = *Edge*
Path length is the number of relationships (links) between source and destination. A path in a group (network) is a sequence of individuals

(vertices) traversed by following relationships (links) from one to another across the group (network).

Geodesic path is the shortest path, in terms of number of relationships (links) traversed, between a specified pair of individuals (vertices). Two unique paths can tie for the title of shortest (Newman, 2008).

2.2 Defining the Network

How the network is defined is critical for meaningful analysis. The concept of topological distance means that interaction between individuals need not be mutual or symmetric. For example, individual A may track its two closest neighbors B & C, but individual B may track its closest neighbors D & E. We use in-degree (reception) as the basis for defining the network, whether a relationship (link) exists between two individuals and, if so, the direction information flows. Information flows towards the receiving individual. In other words, a transmitting individual is not concerned with whether information it emits is used by others, it is solely concerned with using information it receives.

2.3 Metrics

Centrality is a key attribute in the structure and function of networks. There are several ways to describe centrality, a quantity describing an individual's structural importance in a group (network). One measure is *vertex betweenness centrality* (hereafter also referred to as simply *betweenness centrality*): the number of geodesic (shortest) paths between every pair of other group (network) members on which the focal individual lies (Wey et al., 2008). Betweenness centrality is a measure of the influence of individuals in a group over the flow of information between others. Thus, it is closely related to the concept of "load", which quantifies the load of a vertex in the transport of data packets along the shortest pathways (Goh et al., 2001). Individuals with the highest betweenness fall on the boundary between subgroups (communities) in the group, serving as brokers between communities (Lusseau and Newman, 2004). In sociology, betweenness centrality quantifies how influential a given individual in a society is (Freeman, 1977). Betweenness centrality can be viewed as a measure of network resilience (Newman, 2003).

The second metric we use is *average shortest path* length: the average of all geodesic paths between all pairs of individuals in the group (network). This metric relates to the speed with which information can propagate over the shortest paths within the group (network).

2.4 Numerical Swarms

We use four numerical swarms to explore the range of spatial orientations observed in nature presently afforded by our numerical models. Three of the simulations (Figs. 1-3) are variants of our swarm model, presently 2-D, based on elementary optical information processing (Lemasson et al., 2008), which facilitates far-improved biological realism over existing swarm models. For diversity, we also include a 3-D swarm (Fig. 4) generated using the principle of "metric distance". The method used to generate the swarm is not germane to this paper, as both models generate basic emergent spatial orientations and structures that are observed in nature. The swarms are all analyzed as networks defined through topological distance and in-degree (reception) of information flow.

2.5 Analysis

Exploring networks that are dynamic in time and space is more difficult than for static networks. The spatial structure of the group (network) changes often and rapidly with time, with no single snapshot in time being necessary representative of the general properties of the system. In nature, the collective may actually exploit these moment-to-moment changes, with emergent properties shaped by evolutionary pressure without constituent individuals having to be cognitively complicit. To distill multiple dimensions of information simply, we plot the average vertex betweenness centrality and average shortest path for our four numerical swarms versus time for topological distances of one to seven neighbors.

3. RESULTS

Generally, in moving from a topological distance of two to three neighbors the average shortest path decreases most intensely. Over this same interval there is a corresponding increase in average vertex betweenness centrality. With further increases in topological distance both the average shortest path and average vertex betweenness centrality decrease, yet less appreciably.

More specifically, for the numerical swarm in Fig. 1 the greatest drop in average shortest path occurs between a topological distance of two to three neighbors, while the peak average vertex betweenness centrality occurs at a topological distance of three to four neighbors. In Fig. 2, average shortest path decreases somewhat linearly with increasing topological distance. The peak average vertex betweenness centrality generally occurs at six neighbors, with some time periods having peak values at five or seven neighbors. In Fig. 3, as in Fig. 1, the greatest drop in average shortest path occurs moving from a topological

distance of two to three neighbors. Peak average vertex betweenness centrality occurs at a topological distance of three neighbors. In Fig. 4, as in Figs. 1 and 3, the greatest drop in average shortest path occurs moving from a topological distance of two to three neighbors. Peak average vertex betweenness centrality is associated with a topological distance of four neighbors under the swarm formation, four to five neighbors under the torus formation, and three neighbors under the polarized formation.

In summary, the greatest decrease in average shortest path occurs moving from a topological distance of two to three neighbors (with exception of Fig. 2). Average shortest path decreasing asymptotically towards a minimum found at the maximum topological distance. In contrast, average vertex betweenness centrality initially increases with increasing topological distance, peaks at an intermediate topological value, and then decreases with further increases in topological distance (with possible exception of Fig. 2).

4. DISCUSSION

Average shortest path can be viewed as a metric describing the relative speed of information propagation within a group, with lower values of average shortest path reflective of high transfer rates across the group due to fewer numbers of individuals required to fully propagate the information. Betweenness centrality can be viewed as a measure of network resilience (Newman, 2003), with higher average vertex betweenness centrality reflecting lower network resilience because more paths of communication pass through the same number of individuals necessary to fully propagate information amongst the group. Elevated average vertex betweenness centrality would likely be due to (a) a few individuals with very high “loading” of information, (b) a larger number of individuals all with elevated loading, or (c) a combination of (a) and (b). Regardless, higher loading on an individual means that attack or failure of that individual has greater impacts on the propagation of information with the group than if the information loading (measured as vertex betweenness centrality) is lower.

Results suggest the intriguing possibility that a topological distance of three neighbors may largely provide the speed of information transfer required, with spatial structure or additional topological distance used for increasing network resilience when needed. For instance, the torus formation (Fig. 4) often observed of species under predation threat greatly increases network resilience associated with a topological distance of three neighbors. At the same topological distance, the highly polarized formation (Fig. 4) yields much faster information propagation speeds, yet the lowest network resilience. It is possible that the polarized formation is best suited for migration absent predation threats, when the need to warn of a yet unrealized threat is greatest. When a threat first emerges, the low average shortest path suggests the polarized formation has the ability to quickly transmit this information. One plausible response is increasing group (network) resilience through the torus formation, as insurance against the imminent loss of constituent members.

This analysis provides some insight into the theoretical potential of information transfer. This potential is subject to the benefits and costs imposed by ecology (Lemasson et al., 2008). Information in real systems transfers imperfectly so real systems may require more redundancy than is ‘theoretically’ required to achieve a certain level of performance. It is also possible that information in real systems transfers more efficiently through other pathways not immediately intuitive.

CONCLUSIONS

Results suggest the intriguing possibility that a topological distance of three neighbors may largely provide the speed of information transfer required, with spatial structure or additional topological distance used for increasing network resilience when needed. Of the three critical questions we asked, the goal of this paper was to begin answering (1) how many neighbors should be tracked by an individual in a swarm for the collective to realize a maximum efficiency in information transfer. Values in the literature range from three to seven. Our results corroborate the finding of three to four in Luck and Vogel (1997), Vogel et al. (2001), and Bays and Husain (2008), based on limits of visual working memory. Interestingly, this is at the low end of the range of values offered in the literature. Also, this finding supports our use of optical information processing to infer traffic rules within the collective to improve biological realism over existing swarm models (Lemasson et al., 2008) as a means to begin answering the far more complex remaining questions: (2) how are the few neighbors tracked discerned from the collective of many neighbors, and (3) what tradeoffs exist for (1) and (2) under attack and failure scenarios. Answers to these questions are critical to the engineering design of bio-inspired artificial networks robust under attack and failure scenarios.

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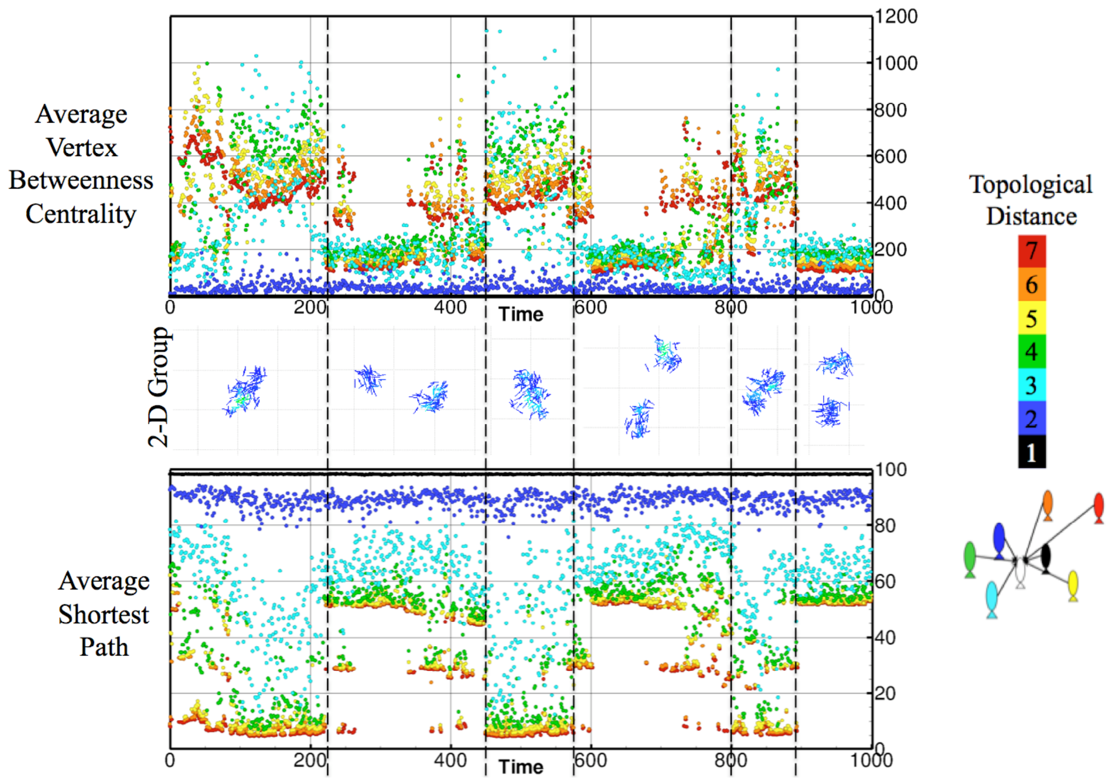

Fig. 1. Two-dimensional group (network) exhibiting fission and fusion.

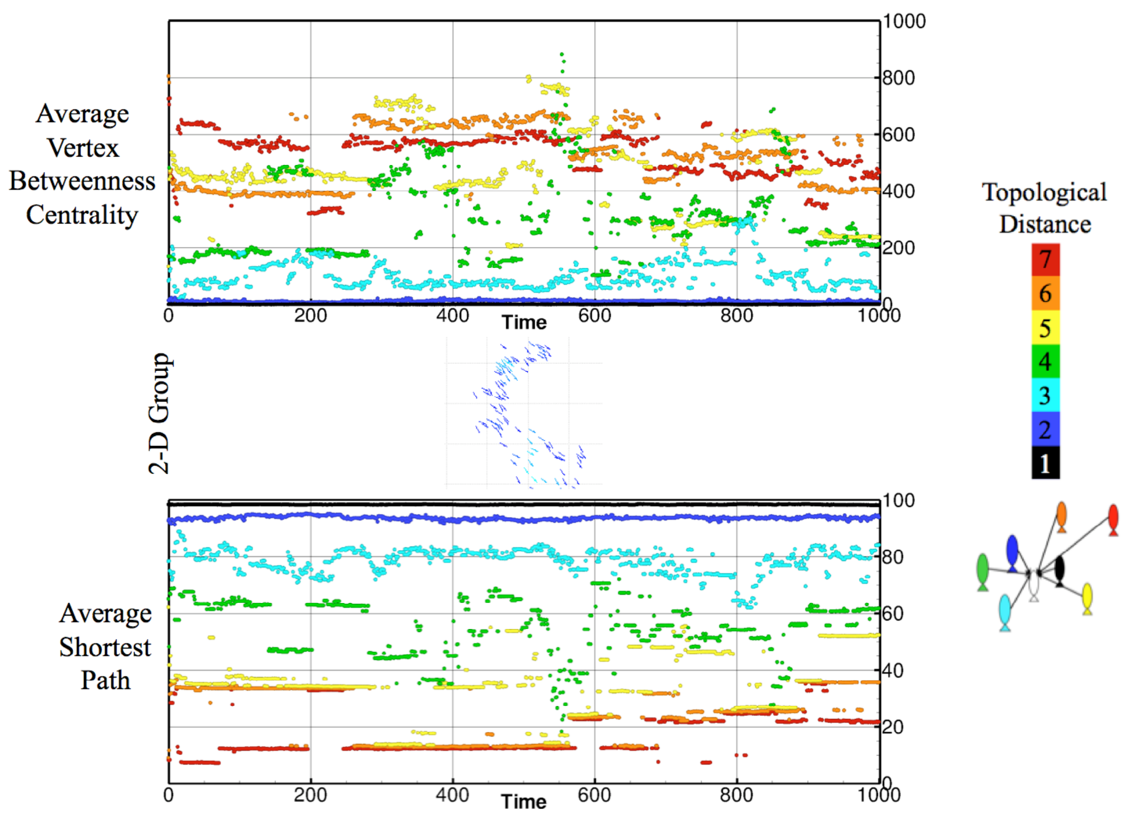

Fig. 2. Two-dimensional group (network) exhibiting high polarization and loose cohesion.

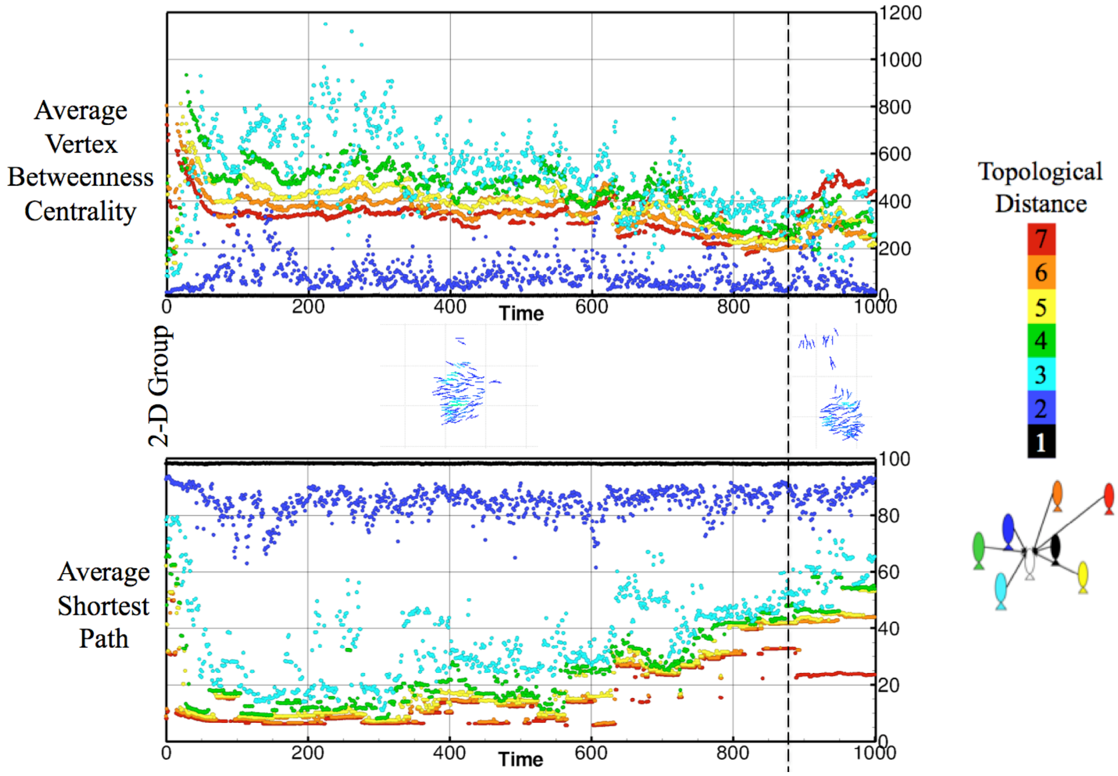

Fig. 3. Two-dimensional group (network) exhibiting mostly high polarization and cohesion.

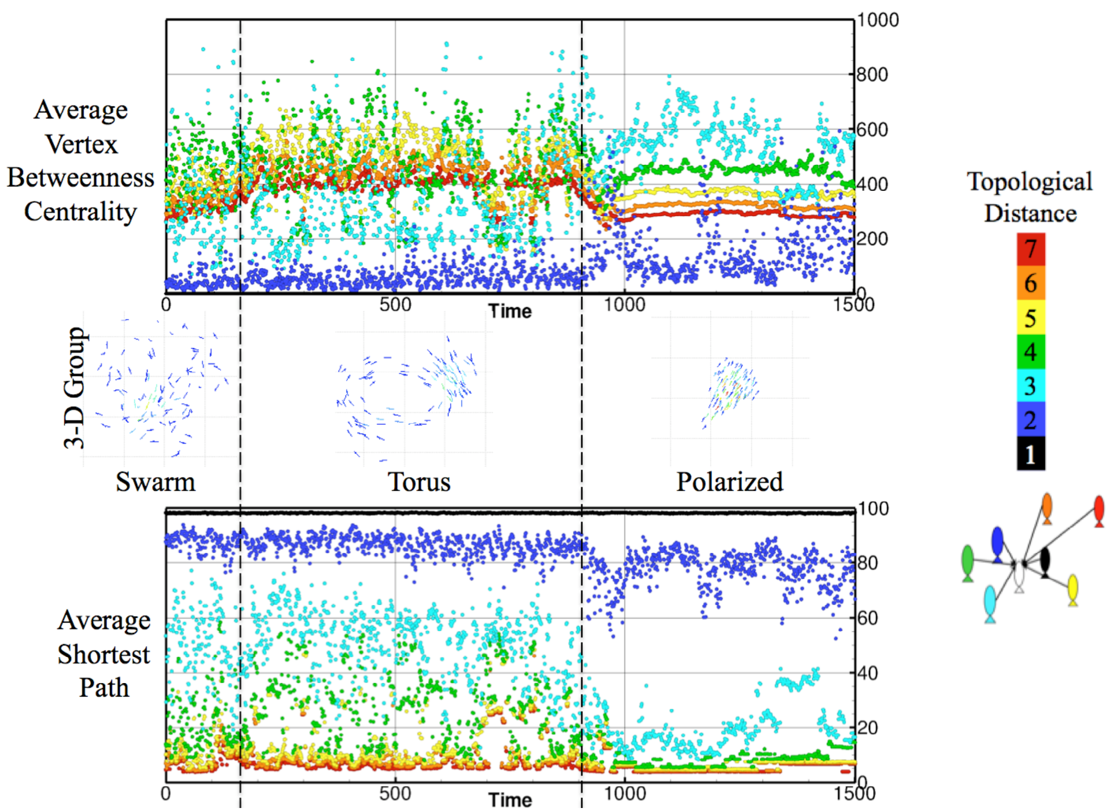

Fig. 4. Three-dimensional group (network) exhibiting non-directional swarming, torus, and then high polarization.

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